Demographic variation in active consumer behaviour: Who searches most for retail broadband services?

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Abstract

Consumers who actively search for better broadband deals may benefit from lower prices or improved service quality compared to those who do not. If, however, consumers differ in their propensity to engage with the market and actively search, these potential benefits may not accrue equally. This paper investigates differences in consumer search activity for telecommunications services across small geographic areas. We exploit rich and novel data from a commercial price comparison site to explore the dispersion of consumer search in the Irish retail broadband market, while controlling for supply-side variations. By linking geo-coded searches to census data on small area socio-economic characteristics, we identify the areas where most search originates and can thus characterise the socio-economic and demographic groups to whom the benefits of search are most likely to accrue. We find evidence that areas populated by many highly educated, married people, commuters, mortgage holders, and retirees are among the most active in search. In contrast, those areas in which many older people, farmers, low-skilled workers and students reside give rise to significantly fewer consumer searches.

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1. Introduction

Liberalisation of retail broadband markets has allowed competition to develop in this sector. Competition provides well-known societal benefits by putting pressure on suppliers to offer better combinations of price and quality. It has potential to boost the penetration of broadband services (Bouckaert, van Dijk, & Verboven, 2010; Dauvin & Grzybowski, 2014; Distaso, Lupi, & Manenti, 2006) and thus may also offer benefits of greater variety and choice of services to more consumers. Even so, the extent of choice in broadband services is not spread evenly across geography. Due to the possibility of economies of density in telecommunications markets, some places have many more suppliers and service offerings than others[1]. Even across national or regional markets where price-setting is relatively uniform and thus the price/quality benefits of competition are shared widely, the societal benefits arising from choice of services are not likely to be spread as evenly.

Independent of supply-side factors, the population of users may vary in the extent to which they exploit the possibilities of retail competition through searching and switching within and between suppliers' offerings. Even in areas served by many suppliers, the expected gains from searching and switching as well as the perceived or actual costs of doing so may vary across individuals and groups. There may also be variations in ability to engage with the market actively.

The literature on behavioural industrial organisation suggests that consumers who are not proactive in seeking out their own optimal packages may be disadvantaged relative to their active counterparts. Firms may adjust their behaviour to exploit myopia. This can result in inefficient market equilibria which disadvantage the unaware consumers. (Gabaix & Laibson, 2006; Grubb, 2015). While some consumers who search may not find better offerings, and others may make poor choices, in general the benefits offered by competition are likely to accrue to groups that engage in search rather than those that do not.

In this paper, we combine data on search intensity with demographic information to explore where, and by whom, consumer search activity for broadband services is most prevalent. To look at the distribution of search intensity, data on consumer searches from a commercial price comparison website in Ireland, Bonkers.ie, are linked to Census data on local socio-economic characteristics of the areas where searches originate. We use regression analysis to unpack the correlated effects on search behaviour of a range of socio-economic characteristics and supply-side factors.

The paper is structured as follows: Section 2 provides background information and reviews the existing literature relevant to the study. Section 3 describes our data and methodology. Section 4 presents and discusses our empirical analysis. Section 5 motivates future extensions to the analysis and Section 6 concludes.

[1] Falch (1997, p.119) notes that network costs per connection decrease as the density of connections increases. In high-density areas, shorter access lines are required and capacity utilisation is higher. Riding, Ellershaw, Tran, Guan, and Smith (2009) estimate the overall cost of deploying various cable technologies in Victoria, Australia and find that they decrease monotonically as household density increases. Grubesic and Murray (2002) highlight that during DSL roll-out in Ohio, service providers were selective about the markets in which they deployed the technology and prioritised geographic areas where there were high densities of potential customers. Grubesic (2006) highlights the extent of the spatial variation in broadband availability that arose across the United States.

2. Background and previous literature

Many factors can affect individual decisions about whether (and how actively) to search for better telecoms deals. A belief that there might be gains from switching should encourage search behaviour. However, even among those who think there are gains to be made, expected gains may be weighed against the actual or perceived cost of engaging in search activities. As a result, variations in the observed aggregate distribution of searches are likely attributable to a complex combination of cost, benefit, and owing to the potential complexity of the decision, psychological factors. In framing our analysis, we draw upon various streams of existing literature.

One important strand of prior research explores consumer decision making when choices are made in the face of actual or perceived costs of searching. The concept of a search cost was introduced to economic discourse through the seminal work of Stigler (1961) which posited that information can reduce uncertainty in consumer decision making but only where the cost of its acquisition is incurred. The now substantial subsequent literature has highlighted the importance of search costs in both theoretical and empirical settings. Indeed, in contemporary work, search costs often emerge as more important than actual or perceived switching costs. For example, Wilson (2012) suggests that the anticipation of search costs may have greater influence in deterring a potential switcher from doing so than switching costs. This is because engaging in an investigation about new products and services incurs a cost with certainty whereas any costs associated with the switching process itself are only incurred conditional on finding a better deal and deciding to act upon it. This relative importance of search costs is confirmed in empirical applications across various markets. In a study of the U.S. car insurance market, Honka (2014) shows that estimated search costs are relatively more important drivers of customer retention when compared to switching costs and customer satisfaction. Similarly, Giulietti, Price, and Waterson (2005) model the probability of switching suppliers in the U.K. residential gas market and find that proxies for search costs are more important than consumers' perceptions of the cost of switching. The perceived cost of information search is also shown to be an important driver of a positive attitude to switching in Gamble, Juliusson, and Gärling's (2009) multi-market study of Swedish consumers, which included the market for landline telecoms. Gärling, Gamble, and Juliusson (2008) provide further experimental evidence that improving the quality of information provided to consumers increases switching activity in a fictitious electricity market. Such findings have prompted suggestions among their authors that policy interventions amounting to reductions in search costs could be used as a means to increase switching activity (Gamble et al., 2009; Gärling et al., 2008; Giulietti et al., 2005).

Of particular interest to the current work is the possibility of systematic heterogeneity in search costs across different socio-economic and demographic groups. Indeed, it is plausible that search costs may affect certain individuals differently. A selection of existing studies test for such variation across a number of market contexts. Most do so as a secondary analysis following estimates of a theoretically grounded search cost distribution. For example, De los Santos (2018) uses both consumer search data and information on transaction prices to model the search cost distribution for online book sales. The author then explores heterogeneity by regressing search duration and the number of firms visited by a searcher on selected demographic variables. In this market context, broadband users, those aged between 30-34 or 55-64 and Asians appear to search across more firms. Conversely, those in the highest income category (and consequently those with the highest opportunity cost of time) exhibit a decreased propensity to engage in search. Similarly, Yilmazkuday (2017) uses zip code level price data to estimate the search cost distribution for gasoline in the US. Estimates are based on a theoretical non-sequential search model. A second stage analysis regresses the expected number of searches from the theoretical model on various zip code level characteristics. Along with some market specific results, the study finds that more searches are expected to originate from areas which on average have lower income, higher population density, short average daily commutes, or more female, African Americans or Asian workers.

A parallel stream of existing literature could provide insight as to why the benefits accrued to individuals as a result of searching could differ, particularly in the case of broadband and telecoms packages. Certain regions, groups or individuals may use the internet and other telecoms services in fundamentally different ways and with different intensities. A heavy service user likely to exhibit a higher propensity to search than a consumer who only has occasional need for it since his/her potential payoff from doing so is likely greater. Existing literature has established such fundamental differences in usage patterns in the case of broadband internet. In particular, education and income are commonly found to be positive correlates of internet adoption and use (Horrigan, Stolp, & Wilson, 2006; Montagnier & Wirthmann, 2011; Roycroft, 2013). Horrigan et al. (2006) also find that being a parent, married or employed can predict internet access in certain circumstances. Even beyond demographics, the same work notes that the economic and population structures of a locality can be confounding factors in the prevalence of internet use. Furthermore, there is evidence that a minority of consumers have not and do not intend to adopt broadband services at all. In a survey of such non-adopters in Carare et al. (2015), almost two-thirds of respondents assert that they have no intentions of adopting at a subjectively acceptable price point. Among this group, however, the stated likelihood of adopting in the future does vary, again, by demographic group. For example, households whose heads are under the age of 40 and those with children under 18 exhibit slight increases in willingness to subscribe in the data. In contrast, retirees are, on average, less likely to report that they would consider a subscription.

Supply-side considerations could also provide explanations for systematic differences in the benefits of searching across geography. Broadband diffusion has not occurred uniformly across space. Indeed, its pattern may be related to various regional factors such as the presence of local loop unbundling, population density, education levels, income, (Lee, Marcu, & Lee, 2011) or the existence of local competition (Bouckaert et al., 2010; Distaso et al., 2006). As a result, the set of services available to the consumer will vary purely based on the location from which one is searching. Data on the pattern of broadband penetration (outlined in Section 3 below) highlight that this is, indeed, the case in Ireland. If consumers become cognisant of poor service quality in a local area, expectations of gains from searching may be revised downward and the propensity to search may decrease accordingly.

Even where the costs or benefits of search do not objectively differ across groups or individuals, the perception of their existence or severity may still vary. For this reason, many existing empirical analyses of consumer interactions with various markets turn to attitudinal measures and subjective proxies of costs and benefits in attempt to gain an understanding of consumers' trade-offs. In a particularly relevant example, Waddams Price and Zhu (2016) make use of specially commissioned survey responses as subjective measures of the costs and benefits of both searching and switching. The paper models the probabilities of having searched and/or switched in eight UK markets (three of which are directly related to telecoms) in the three years previous to the survey. Searching and switching are first modelled separately since the underlying motivations for each process may be fundamentally different. Nevertheless, a further model with a combined "searched and switched" outcome is also reported for contrast. Respondents' expectations of gains from searching/switching and their expected time commitment required to engage in either activity are used, along with demographic information, as key explanatory variables.

Expected gains are found to be positively associated with both searching and switching while the expected time to switch has a negative association with both activities. Interestingly, the expected time taken to search does not appear to affect the probability of doing so. In terms of demographic factors, a U shaped relationship is identified between age and the probability of searching/switching, with younger and older respondents engaging more than those of middle age. The authors do, however, recognise some uncertainty over this functional form because of potential selection issues. Those on higher incomes are found to switch less, a result which is consistent with an established hypothesis in the literature that such individuals should be deterred from activity due to a high opportunity cost of time (e.g. Stigler, 1961). Search shows a similar negative association with income, but with only marginal statistical significance. Males are also shown to be less likely to search and/or switch than females, but no direct association with educational attainment is identified. The authors further note significant variation in their results across market contexts and individuals. For example, search activity is less likely in the fixed phone line and call markets than it is in the market for electricity.

More broadly, the literature that seeks to understand consumer activity in regulated markets (most notably telecommunications and energy sectors) is growing. However, to date the predominant focus of empirical work in this area has been directed at consumer switching. While the above discussion serves to highlight the importance of analysing consumer searching directly, insights from studies of consumer switching can provide context to the analysis that follows here. In particular, it is noteworthy that socio-demographic variables have frequently featured as potential drivers of switching activity. If differences in switching behaviour are shown to be systematic across these variables, then it is possible that some of the same group-wide patterns will partially drive differences in search behaviour in the analysis of this paper (since consumers may engage in search before a switch). Consensus, however, has not been reached on the effect of many such variables since the results have an apparent sensitivity to context. For example, Gamble et al. (2009) find that males tend to have more positive attitudes to switching than females across a number of markets and the results of Ranganathan, Seo, and Babad (2006) suggest that they are also more likely to switch in the mobile telecoms market. Other studies, however, find no such gender differences in propensity to switch in telecoms or energy (Burnett, 2014; He & Reiner, 2017) and, as noted previously, Waddams Price and Zhu (2016) find the opposite relationship in their multi-market study. Similarly, the relationship between switching and income differs across studies with negative (Waddams Price & Zhu, 2016), inverted U (Giulietti et al., 2005), small positive (Ek & Söderholm, 2008) and insignificant (He & Reiner, 2017) relationships identified in different contexts. The relationship between switching and age is perhaps a little more stable with a number of studies identifying a negative association (Burnett, 2014; Lopez, Redondo, & Olivan, 2006; Ranganathan et al., 2006). Educational attainment also appears not to have a direct relationship with switching (Giulietti et al., 2005; Waddams Price & Zhu, 2016) albeit that Gamble et al. (2009) find that those with higher levels of education tend to have more negative attitudes to switching. Lunn and Lyons (2018) note similar inconsistency in the effects of background characteristics on switching intentions in telecoms and suggest that it results from the complexity and content specificity of the individual switching decision.

Our approach in this study is to infer the characteristics of individuals that are engaged in search for telecommunications services from the socio-economic attributes of the areas in which they live. We contribute to the existing literature in three distinct ways. First, we contribute a direct analysis of consumer search for electronic communications services. This explicit focus is uncommon in the existing literature of consumer activity in telecommunications, which, to date, has principally been concerned with consumer switching. Second, our analysis explores a unique and novel dataset originating from a commercial price comparison site. These data offer a new perspective to the literature as they detail actual online search activity and are not reliant on survey-style or self-reported measures. Our analysis can be seen as a valuable complement to existing survey-based studies. Where our results coincide with those obtained from alternative methodologies, the evidence that true effects are being observed may be regarded as more persuasive. Finally, and perhaps most importantly, by profiling the average users of a commercial price comparison site for broadband services, we provide insight on the socioeconomic gradient of the site's usage. Given calls for simplification of the consumer switching process (Gamble et al., 2009; Gärling et al., 2008; Giulietti et al., 2005), it is important from a policy perspective to understand to whom the potential benefits of an online simplification tool, and, ultimately of consumer search, are most likely to accrue. Due to limitations in the available data, our study does not attempt to explicitly disentangle the individual mechanisms that may induce a consumer to search more or less.

3. Data and methods

In this section, we describe the spatial and temporal characteristics of the data, outline the characteristics of the dependent variable and econometric methods used, and conclude with a discussion of the explanatory variables.

3.1. Spatial and temporal dimensions of the data

We observe searches that were initiated by users of the Bonkers.ie price comparison website during the 314 days from 17 August 2016 to 27 June 2017. Only search entries accompanied by valid spatial locations are included in our analysis (72,113 searches out of a total of 171,889)[2]. This spatial information takes the form of Eircodes, building-specific postcodes recently introduced in Ireland. In order to search for broadband services, users of the Bonkers.ie service were asked to enter their Eircode to allow the service to identify which broadband plans were available in their locality. For the analysis in this paper, we map each building location into its relevant Small Area, an administrative unit of which there are 18,641 in Ireland. The Small Area is a convenient unit of analysis since it is the most spatially dis-aggregated level at which many socio-demographic variables are available from Ireland's national statistical agency, the Central Statistics Office (CSO). The exact data we use are drawn from the *Small Area Population Statistics (SAPS)* which were collected as part of a national census in April 2016.

3.2. Dependent variable

Our primary outcome of interest is search intensity, which we calculate as the number of searches per 100 households in each Small Area. Our models seek to explain local search intensity as a function of many socio-economic and demographic factors, and we use regression analysis to measure the relative importance of these factors. Search intensity is expressed as a ratio of searches to the local number of households to enhance comparability. Small Areas vary significantly in size, and larger places are likely to have more searches simply because the pool of potential searchers is larger. Table 1 below shows descriptive statistics for this variable, its components and other continuous variables used in our analysis.

[2]This number also excludes searches that arise from excessive use of a single IP address. These are likely to occur as a result of internal system testing etc. and are not likely to relate to individual searchers seeking retail packages for personal use. We drop searches originating from IP addresses that fall above the 95th percentile of IP usage.

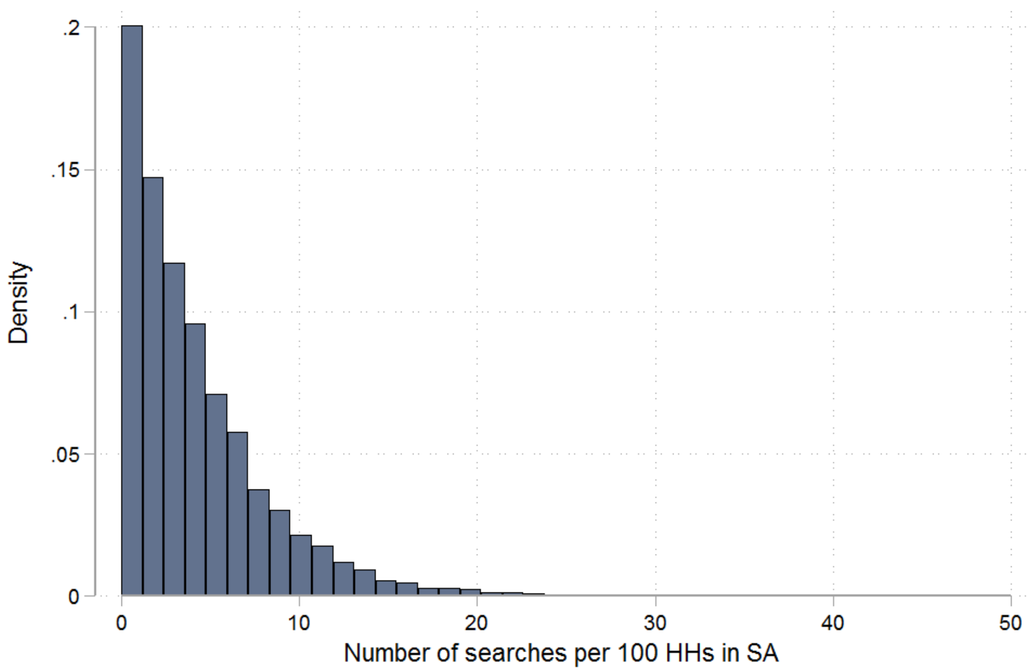
Table 1: Descriptive Statistics: Continuous Variables

	N	Mean	St. Dev	Min	Max
Search Intensity (Searches/100 HH)	18,641	4.15	4.07	0	50
Number of Searches	18,641	3.87	3.97	0	43
Persons	18,641	255	88.2	50	1,629
Households	18,641	91.1	24.1	22	536
Area (Sq. Km)	18,641	3.77	7.17	.00108	163
Population Density (Persons/Sq. Km)	18,641	3,465	6,225	.557	273,698

Source: Bonkers.ie & Census Small Area Population Statistics 2016

Figure 1 shows how search intensity is distributed. Many Small Areas had no searches in the sample period, giving rise to zero values for the search intensity. While many others did have searches, the frequency declines steadily across positive values and tends towards minimal values above about 10 searches per 100 households.

Figure 1: Histogram of Search Intensity by Small Area



3.3. Estimation methods

As noted, the dependent variable of interest has a zero-lower bound. We use a Tobit estimator to account for the censored distribution of the data. It seems likely that many places had a low aggregate propensity for searches, but due to the discreteness of search behaviour, it was not possible to register search intensities below zero. The Tobit estimator allows for the possibility that individuals (and hence groups) have a latent propensity to search that only leads to an observable search event if the propensity exceeds some threshold level. The model is specified as follows:

$$S_j^* = I_j'\beta_1 + x_j'\beta_2 + \varepsilon_j \quad j = 1, ..., 18,641 \tag{1}$$

$$S_j = \begin{cases} S_j^* : \text{ if } S_j^* > 0 \\ 0 : \text{ if } S_j^* \leq 0 \end{cases} \tag{2}$$

where S_j is the observed number of searches per 100 households in Small Area j, I_j measures the share of households with various types of internet access in Small Area j, x_j contains a range of socio-economic and demographic characteristics of Small Area j and $\varepsilon_j \sim IID\left(0, \sigma_\varepsilon^2\right)$.

Because coefficients of the latent variable model do not necessarily have a direct and meaningful interpretation, we instead report marginal effects. Specifically, we present the unconditional marginal effect on the expected value of S_j of a change in any particular x_{jk}, calculated at the means of the independent variables. Formally:

$$\mathbb{E}\{S_j\} = x_j'\beta\Phi\left(\frac{x_j'\beta}{\sigma}\right) + \sigma\phi\left(\frac{x_j'\beta}{\sigma}\right) \tag{3}$$

$$\frac{\partial\mathbb{E}\{S_j\}}{\partial x_{jk}} = \beta_k\Phi\left(\frac{x_j'\beta}{\sigma}\right) \tag{4}$$

where $\phi(.)$ and $\Phi(.)$ are the cumulative distribution and probability density functions of the standard normal distribution respectively.

3.4. Explanatory variables

Section 2 highlights many socio-economic factors that might be expected to affect search intensity. Many of these factors are, however, likely be correlated with one another, making it difficult to distinguish their individual contributions. To help manage this complexity and identify which types of effects are likely to be most important, we run two regression models with different sets of explanatory variables. These can be broadly characterised as focusing on 1) variables that describe household characteristics and 2) variables that describe individual characteristics. A combined model is also presented. This third model will allow us to explore the ways in which the previous two are interconnected and potentially identify if and where associations are being obscured by the likely collinearity between explanatory variables.

Across the models, we include proxies for availability and take-up of internet services, each of which should have a direct effect on incentives to search for better service. Availability is proxied by a spatial dataset collected at the end of Quarter 2, 2017 as part of the preparation of Ireland's National Broadband Plan (NBP), a long-term government initiative to bring broadband at speeds of over 30Mbps to homes and businesses across the country. The dataset divides the country into three colour-coded regions. The 'Dark Blue' region indicates places where commercial operators already provided high-speed broadband. The 'Light blue' region denotes areas where this standard of service is not yet available but where operators had committed to provide it over a specified time-frame.[3] The 'Amber' regions are those expected to require state intervention to attract highspeed broadband network provision. They tend to

[3]These improvement works had not commenced during our period of analysis.

have poorer quality broadband provision.

Our second set of controls included in all models focuses on the rate of broadband take-up by households in each Census Small Area. This is based on a census question that asked whether or not households had access to the internet, either through a broadband connection or otherwise.

We also calculate the population density in each Small Area in persons per square kilometre. As well as impacting on broadband network availability and the number of services likely to be offered (Lee et al., 2011), in principle population density might have some influence on local residents' average propensity to search. It is included across the models as a five-level categorical variable.

Tables 2 and 3 set out descriptive statistics for the categorical variables relating to households and individuals used in the models to follow. These data capture the share of each Small Area's population (a count of either households or individuals) in a given category. It should be noted that we do not observe the characteristics of each individual searcher and as such, any associations identified by our empirical analysis are inferred from local area averages. We discuss the explanatory variables in more detail under the models in which they are included.

Variables describing household characteristics

The CSO's social class variable is based on occupation, ranging from professionals and managers to unskilled labourers. Social class may affect search propensity directly, e.g. through skills and behaviours acquired at work, but it may also do so indirectly as an indicator of income level. As highlighted, the literature suggests that a measure of income could play a key role in our analysis, although the expected direction of any income effect remains ambiguous. Those in higher income groups have an increased propensity to take out broadband subscriptions and thus are likely to benefit from search. Equally, however, they may have a high opportunity cost of time and thus be disinclined to engage with the market. Since income information is not available at Small Area level, proxies like social class and educational attainment are used in attempt to capture any income-related effects.

Family composition is a set of categorical variables sorting families by whether children are present in the household and by the ages of other household members. The propensity to search could vary across these family structures since usage intensity likely does. It is possible that the presence of children in the household could lead to increased use of broadband for entertainment purposes. Younger families may also be more price sensitive and thus have relatively more to gain from active search.

Housing tenure, including whether people own their residences or rent them, could well have implications for whether they are able to switch service provider and how much stake they feel they have in choosing the best option. Perhaps having a long-term tenure encourages attention to putting more optimal services in place, or perhaps experiencing more turnover in residences induces people to look more often at which would be the best service provider. Housing status, which characterises the physical structure of residential dwellings may equally have implications on the occupants' ability and propensity to switch provider.

Table 2: Descriptive Statistics - Variables Describing Household Characteristics (18,641 Small Areas)

	Mean (%)	St. Dev (%)	Min (%)	Max (%)
Internet Access				
NBP Amber	21.7	32.3	0	100
NBP Dark Blue	68.5	42.3	0	100
NBP Light Blue	9.79	20.6	0	100
Broadband	69.7	15.6	2.5	100
Other Access	8.08	6.81	0	51.4
None	19.1	11.3	0	76.3
N.S.	3.13	3.64	0	97.5
Family Profile				
Pre-family	10.5	12.5	0	100
Empty Nest	10.2	5.51	0	85.7
Retired	10.3	7.75	0	75
Pre-school	10	6.12	0	100
Early Sch.	11.5	6.36	0	100
Pre-adolescent	10.9	5.78	0	58.5
Adolescent	11.9	5.95	0	52.2
Adult	24.6	11	0	100
Housing Status				
House/Bungalow	86.6	24.5	0	100
Flat/Apt.	11.6	24.2	0	100
Caravan	.274	1.21	0	58.7
N.S.	1.29	2.05	0	97.5
Housing Tenure				
Owner with Mortgage	30.9	15.2	0	90.9
Owned Outright	36.9	19.3	0	92.5
Private Rental	18.2	17.8	0	95.2
Local Auth. Rental	8.16	13.9	0	100
Voluntary Body Rental	.93	3.72	0	66
Free of Rent	1.7	1.91	0	85.4
N.S.	3.12	3.88	0	97.5
Social Class				
A (Emp./Manage.)	14	7.69	0	56.8
B (Higher Prof.)	6.52	5.65	0	46.3
C (Lower Prof.)	11.7	5.76	0	46.4
D (Non-manual)	18	6.4	0	50
E (Manual skilled)	8.76	4.62	0	31
F (Semi-skilled)	8.3	4.61	0	46.4
G (Unskilled)	3.72	3.15	0	32.1
H (Own A/c Work.)	4.82	2.95	0	26.7
I (Farmers)	5.34	8.34	0	55.2
Other	18.9	10.9	0	100

Source: Census Small Area Population Statistics 2016 & National Broadband Plan Map.

Table 3: Descriptive Statistics - Variables Describing Individual Characteristics (18,641 Small Areas)

	Mean (%)	St. Dev (%)	Min (%)	Max (%)
Age Category				
Under 18	24.1	8.27	0	57
18-24	8.2	6.08	0	99.5
25-34	14.1	8.29	0	68.7
35-44	15.4	5.14	0	38.1
45-54	13.1	4.01	0	31.4
55-64	11	5.02	0	54
65+	14.1	8.85	0	85.7
Marital Status				
Single	53.4	9	24.9	100
Married	37.4	8.89	0	65.2
Separated	2.57	1.57	0	22.3
Divorced	2.28	1.5	0	18.3
Widowed	4.31	3	0	37.6
Place of Birth				
Ireland	82.2	12.2	14.3	99.7
UK	6.23	4.29	0	79.4
Poland	2.45	4.02	0	56.5
Lithuania	.701	1.61	0	29.4
Other	3.26	4.42	0	47.2
ROW	5.15	6.28	0	68.9
Employment Tenure				
At Work	53.3	11.8	.59	93.1
Searching: First Job	.846	.927	0	12
Unemployed	7.27	4.88	0	44
Student	11	6.52	0	97.9
Homeworker	8.14	2.97	0	26.1
Retired	14.8	8.64	0	78.9
Disabled	4.25	3.21	0	47.7
Other	.359	1.26	0	56.1
Educational Attainment				
Primary	10.9	7.55	0	52.8
Lower Secondary	14.5	6.65	0	100
Upper Secondary	18.5	5.17	0	100
Certificate	19.7	5.85	0	55.9
Degree+	28.4	15.9	0	100
None/N.S.	8	7.19	0	100
Commute Duration				
Less than 15 mins	33.3	13.1	0	90.2
15-30 mins	28.5	9.01	0	81.5
30-45 mins	16.9	7.34	0	46.2
45-60 mins	5.65	3.62	0	25
60-90 mins	5.79	3.89	0	30.1
90+ mins	2.26	1.86	0	15.7
N.S.	7.69	5.87	0	98.9

Source: Census Small Area Population Statistics 2016

Variables describing individual characteristics

Age groups may have differing propensities to search for broadband services both because they may use these services in different ways due to varying habits, skills, and life experiences and because they may have differing attitudes towards consumer search generally. The census data allows us to proxy the prevalence of different age groups making broadband search decisions with the local prevalence of each of seven age categories in a given area.

Employment and education, like social class, may partly serve as proxies for income. However, each may also have direct effects on switching propensity by conferring information and skills relevant to consumer decision making.

Most Irish residents are Irish-born, but all Small Areas have at least some foreign-born residents. It is possible that foreign-born residents use the internet differently due to their international links or have different past experiences of consumer switching. We thus include the shares in each area of residents from several other jurisdictions.

While there is little information in the Census on the time pressures households face (i.e. whether the time available for activities such as consumer search is limited), we try the time spent commuting as a proxy for this. The likely direction of impact for this variable is uncertain since there is also a possibility that commuters taking public transport could use their commuting time for search activities (i.e. using mobile devices).

If consumers have recently moved into an area they may be more likely to actively search for a new broadband offering. We test this possibility by including a variable which details whether or not an individual was resident in the Small Area exactly 1 year prior to the census. We compare the share of residents who have remained at the same address against shares of those who have taken up residence after moving from elsewhere in the country or abroad.

Finally, perhaps there are local factors that drive propensity to switch, apart from the effects of population density on availability and choice of broadband service. To check for such unobserved factors we control for county of residence in all models.

3.5. Data Selection

Given the available data, it is not possible to test whether the searchers captured in our data are representative of searchers in Ireland generally. Being drawn from one price comparison website provider, our data do not achieve universal coverage of online searches for broadband packages over the study period. During this period, there were a small number of other price comparison sites that could have been used by searchers. Some consumers doubtless carried out searches by going directly to the websites of broadband providers or (for some services) by visiting physical retail outlets. We also capture only the subset of searches on Bonkers.ie that had valid location information (see section 3.1 above). Finally, it is possible that Bonkers.ie attracted systematically different types of searchers than other websites or channels due to its branding or promotional activity.

It should be noted, however, that bonkers.ie is one of the two largest price comparison websites in the Irish market. It has also held accredited status by a regulator in one of the markets it serves in Ireland for longer than any of its competitors,[4] giving it a longer time-frame than any other site to build its brand. Furthermore, communications with Bonkers.ie management suggest its marketing activities are unlikely to create a selection issue. Given the company's prominence among online search providers, the limited set of alternative search options in the Irish market and the volume of searches observed, it is likely that the findings we report are reflective of systematic variation in the propensity to search rather than variation in the channel via which search takes place.

4. Results and discussion

In this section, we report the results from three regression specifications, each focusing on a different set of control variables. The common dependent variable in all models is our measure of Small Area search intensity. In addition, all regressions include our controls for internet availability and usage as well as the five-category variable capturing the quintile of population density in which each Small Area lies. Since all independent variables are measured in shares and so must, by construction, lie on the interval $[0, 1]$, the reported coefficients in all models should be interpreted as marginal effects arising from a change from 0 to 1 in the share of the relevant explanatory variable *ceteris paribus*.

Across the models (Tables 4, 5, and 6), search intensity is lower in areas with less broadband availability and take-up. In terms of our access proxy, being in an area where high-speed broadband is not (yet) available is associated with fewer searches. This makes intuitive sense as, by definition, these areas have a narrower range of options for domestic broadband and so there is less need to engage in search to find better deals. The magnitude of this effect is relatively small. The range of coefficients on the NBP variables suggests that the expected decrease in searches is, on average, less than 1.1 per 100 HH. With regard to usage, areas where fewer people have broadband or other forms of internet access also experience fewer searches. This is equally sensible since the need to search for better deals is understandably diminished in areas where many residents have not yet adopted broadband services (and possibly do not intend to). The effect magnitude is also more substantial here, with about 4.5-5 fewer searches per 100 HH (or roughly 1 standard deviation in the observed distribution of search) expected in an area where all households have "other" forms of internet access versus one where all households have broadband. While areas that are poorly served by the NBP likely have some overlap with those in which usage is lower, the fact that the coefficients on both sets of control variables are statistically significant suggests that they may be capturing two distinct effects.

The categorical measure of population density also exhibits a consistent pattern across all of the models. Using the third quintile as a reference category, one sees that there are statistically fewer searches both in the areas with lower density and, indeed, in the top category. However, the magnitudes of these effects are small. The result in the lower quintiles could be a further manifestation of some of the mechanisms noted above. For example, sparsely populated areas may be those with few commercial broadband options, limiting the likely gains from search. The finding that areas with the highest population density have slightly lower search intensity than those with intermediate density is more surprising. These are likely to be the areas with the best coverage and range of services. There may be some influence of the specific mix of network technologies used in these areas. For instance, cable broadband is likely to be more important in these areas than elsewhere, and our broadband availability control does not pick up

[4] The Commission for Regulation of Utilities accredited bonkers.ie in 2012. The site's closest competitor, switcher.ie (originally uswitch.ie) was not accredited until 2013)

Table 4: Marginal effects from Tobit model regressing search intensity on variables describing household characteristics (Small Area shares)

Dependent Variable: Searches/100 HH	(1) $\delta y/\delta x$	Robust SE
Broadband: NBP		
NBP Dark Blue	**[ref]**	
NBP Light Blue	-0.638^{***}	(0.141)
NBP Amber	-0.698^{***}	(0.185)
Broadband: SAPS		
Broadband Access	**[ref]**	
Other Access	-4.465^{***}	(0.397)
None	-2.876^{***}	(0.625)
Population Density		
Quintile 1	-0.252^{*}	(0.150)
Quintile 2	-0.174^{**}	(0.0856)
Quintile 3	**[ref]**	
Quintile 4	-0.136	(0.0901)
Quintile 5	-0.631^{***}	(0.0963)
Family Structure		
Pre-family	3.344^{***}	(0.462)
Pre-School	3.407^{***}	(0.701)
Early School	2.067^{***}	(0.533)
Pre-Adolescent	1.061^{**}	(0.441)
Adolescent	-0.101	(0.487)
Adult	**[ref]**	
Empty Nest	0.666	(0.679)
Retired	-0.423	(0.689)
Social Class		
A (Employers/Managers)	2.257^{***}	(0.701)
B (Higher Prof.)	3.550^{***}	(1.292)
C (Lower Prof.)	3.149^{***}	(1.008)
D (Non-manual)	**[ref]**	
E (Manual skilled)	-3.249^{***}	(0.917)
F (Semi-skilled)	-3.282^{***}	(0.843)
G (Unskilled)	-2.739^{**}	(1.135)
H (Own A/c Workers)	-1.421^{*}	(0.860)
I (Farmers)	-5.769^{***}	(0.805)
Other	-3.087^{***}	(0.516)
Housing Status		
House/Bungalow	**[ref]**	
Flat/Apartment	-0.714^{**}	(0.280)
Caravan/Mobile home	1.028	(1.964)
Not Stated	0.986	(1.283)
Housing Tenure		
Owned Outright	**[ref]**	
Owner with Mortgage	1.671^{***}	(0.522)
Private Rental	-0.995^{**}	(0.474)
Local Auth. Rental	-1.557^{***}	(0.367)
Voluntary Body Rental	0.00985	(0.555)
Free of Rent	-2.268	(1.442)
N.S.	-0.313	(0.724)
County of Residence		
Carlow	-0.501^{***}	(0.103)
Dublin City	**[ref]**	
South Dublin	-0.175^{***}	(0.0459)
Fingal	0.475^{***}	(0.0564)
Dun Laoghaire-Rathdown	0.516^{***}	(0.0520)
Kildare	-0.0553	(0.0649)
Kilkenny	-0.123	(0.111)
Laois	-0.577^{***}	(0.111)
Longford	-0.415^{***}	(0.140)
Louth	-0.470^{***}	(0.0791)
Meath	0.174^{**}	(0.0835)
Offaly	-0.303^{**}	(0.122)
Westmeath	-0.524^{***}	(0.103)
Wexford	-0.408^{***}	(0.122)
Wicklow	0.359^{***}	(0.0644)
Clare	-0.156	(0.120)
Cork City	0.268^{***}	(0.0493)
Cork	0.104	(0.0837)
Kerry	-0.725^{***}	(0.154)
Limerick City	-0.728^{***}	(0.0667)
Limerick	-0.0754	(0.104)
Tipperary North	-0.570^{***}	(0.125)
Tipperary South	-0.261^{**}	(0.118)
Waterford City	-0.0234	(0.0538)
Waterford	-0.606^{***}	(0.0922)
Galway City	-0.306^{***}	(0.0488)
Galway	-0.245^{**}	(0.119)
Leitrim	-0.386^{**}	(0.157)
Mayo	-0.392^{***}	(0.140)
Roscommon	0.00469	(0.154)
Sligo	0.0995	(0.111)
Cavan	-0.541^{***}	(0.129)
Donegal	-0.612^{***}	(0.145)
Monaghan	-0.846^{***}	(0.123)
Observations	18,641	

Notes: Standard errors allow for clustering at the county level. $^{*}p<.1$; $^{**}p<.05$; $^{***}p<.01$

variations in local availability of network types.

4.1. Results for model using household-level characteristics

The focus of the regression reported in Table 4 is on control variables which relate to households. The model treats Small Area search intensity as a function of average family structure, social class, housing status and housing tenure in the area. The common internet and population controls are also maintained. A number of noteworthy associations emerge:

First, the model suggests that an area populated fully by young family structures would expect to make about 1-3.4 additional searches per 100 households (depending on exact family classification) than one populated by the reference adult families. This is consistent with our prior expectations: younger members of a household may be among the heaviest users of domestic broadband for recreational purposes and so this result may indicate a generational effect. Indeed, it is probable that the parents in such households are also younger and could also be heavier users than households of older family structure.

Second, high social class has a strong positive association with the intensity of search for broadband packages. The results indicate that a Small Area populated entirely by social class A to C households would also be expected to make 2.26-3.55 additional searches per 100 households than one with all social class D (non-manual) households. The converse is true in an area populated entirely by E (manual skilled) to G (unskilled) households, where about 2.7-3.3 fewer searches per 100 households are expected. Farming communities are also expected to search significantly less (5.77 fewer searches per 100 HH). These results are particularly interesting.

Recall from the discussion in Section 2, that as a proxy for income the anticipated effect of social class was ambiguous. In other market contexts, higher income groups were found to search less (De los Santos, 2018; Yilmazkuday, 2017). At the same time, however, income and educational attainment are positive correlates of broadband adoption (Horrigan et al., 2006; Montagnier & Wirthmann, 2011; Roycroft, 2013). It appears that the latter effect is that which plays out in our model. It may also be possible that given the likely correlation between social class and education, those among the higher social classes are more aware of the possible gains from switching and are generally better equipped to navigate the market.

Third, in comparison to an area where the population lives in houses or bungalows, one in which people reside in flats or apartments is expected to see 0.71 fewer searches per 100 HH. We suggest that this may reflect the fact that many flats and apartments are privately rented rather than owner-occupied. Tenants may have less scope to influence selection of utility suppliers, reducing their need to engage in search. Equally, if those inhabiting apartments intend to remain in their current accommodation over shorter periods, then the longer-term savings accrued from finding a better broadband deal may be less relevant to them.

Indeed, the results from the housing tenure controls hint at similar mechanisms. 1-1.6 fewer searches are expected in a fully rental area than one where homes are all owned outright. There is also a statistically significant difference between this reference category and areas where resident households are all mortgage holders. The model suggests an increase in expected searches in the latter. Mortgage holders may be somewhat credit constrained and have an increased incentive to search for better internet deals.

In addition to the above, we include a set of county controls, aimed at capturing broad geographical patterns in search intensity across the country. Such differences at the county level appear limited in scale but some tendencies towards more intensive search in more urban counties are observed.

4.2. Results for model using individual-level characteristics

Table 5 shifts the focus from households to a set of control variables which relate to the characteristics of individuals in each Small Area. We include variables describing age, marital status, place of birth, daily commute, employment and education. The age control presents an intuitive result. Areas populated by older people show significantly less search intensity. A hypothetical area inhabited entirely by over 65s would be expected to average 8.6 fewer searches per 100 households than the one populated entirely by the reference group of 35-44 year-olds. Indeed, areas with high shares of people in the reference group are the most active in search, although there is no statistically significant difference in search intensity between them and the two youngest age categories. One can draw some parallels between this result and that of the family structure controls in the previous regression. We thus postulate that a similar generational mechanism might be at play here.

There is some evidence that areas with high shares of married people have more searches than those with more single people, whereas areas with many people originally from outside Ireland have significantly fewer searches than areas where most residents were born in the country. This latter association appears counter-intuitive given that foreign-born internet users might be expected to use these services at least as intensively as Irish-born residents to gain access to content and communications links abroad. Since the greatest differences appear among those originating from non-English speaking countries, the lower search rates could be attributable, at least in part, to actual or perceived linguistic barriers to effective product search via a price comparison site operating in English. The coefficients on the "'residence 2015" variables would also seem to support this hypothesis. While the model expects that an increase in the share of residents who have moved to a given Small Area from elsewhere in the country in the previous year leads to an increase in searches, the converse is true if those new residents have moved to the area from outside of Ireland.

The availability of time to search may be a factor driving the associations seen in the commuting variables. Commuting areas search more than those with more residents that do not commute. A 60-90 minute commuting duration is also associated with a greater increase in searches than shorter journeys. This is consistent with our hypothesis that the commuting duration for those using public transport may offer an individual time to go online and engage in search activity.

While we might also have expected time constraints to drive differences in search intensity across employment status, with areas where most individuals are employed having less time to search, this does not seem to be the case. In fact, areas with most employed residents are those with the most searches expected by the model. It is worth noting, however, that this result may reflect as much about the categories to which the employed are being compared as it does about the employed themselves. Specifically, areas with many students, unemployed, homeworkers or those searching for their first job may also be those who are not directly taking out broadband contracts and thus may naturally have a lower propensity to search.

Perhaps surprisingly, given the finding mentioned earlier that the oldest groups search less than younger groups, being retired is strongly associated with higher search intensity. Such apparently paradoxical

Table 5: Marginal effects from Tobit model regressing search intensity
on variables describing individual-specific characteristics (Small Area shares)

Dependent Variable: Searches/100 HH		
	(2)	
	$\delta y/\delta x$	Robust SE
Broadband: NBP		
NBP Dark Blue	**[ref]**	
NBP Light Blue	-0.855^{***}	(0.149)
NBP Amber	-1.073^{***}	(0.182)
Broadband: SAPS		
Broadband Access	**[ref]**	
Other Access	-4.955^{***}	(0.404)
None	-3.862^{***}	(0.616)
Population Density		
Quintile 1	-0.872^{***}	(0.157)
Quintile 2	-0.363^{***}	(0.0903)
Quintile 3	**[ref]**	
Quintile 4	-0.112	(0.0827)
Quintile 5	-0.565^{***}	(0.0837)
Age Category		
Under 18	-1.296	(1.219)
18-24	-0.909	(0.982)
25-34	-2.340^{**}	(0.958)
35-44	**[ref]**	
45-54	-0.803	(1.015)
55-64	-4.832^{***}	(1.351)
65+	-8.575^{***}	(1.485)
Marital Status		
Single	**[ref]**	
Married	3.789^{***}	(0.660)
Separated	-1.187	(2.188)
Divorced	2.232	(2.339)
Widowed	6.802^{***}	(1.816)
Place of Birth		
Ireland	**[ref]**	
UK	-2.252	(1.420)
Poland	-3.368^{***}	(0.740)
Lithuania	-5.882^{***}	(1.695)
Other	0.217	(0.879)
ROW	-3.508^{***}	(0.783)
Commute Duration		
None	**[ref]**	
15-30 mins	1.429^{***}	(0.505)
30-45 mins	1.430^{***}	(0.376)
45-60 mins	0.755	(0.897)
60-90 mins	3.547^{***}	(1.333)
90+ mins	0.858	(1.519)
N.S.	1.975^{**}	(0.799)
Employment Tenure		
Employed	**[ref]**	
Searching: First Job	-7.529^{***}	(2.300)
Unemployed	-2.817^{**}	(1.245)
Student	-3.525^{***}	(0.690)
Homeworker	-2.729^{**}	(1.063)
Retired	3.643^{***}	(1.290)
Disabled	2.900^{*}	(1.622)
Other	1.297	(1.617)
Educational Attainment		
None/N.S.	-1.514	(0.982)
Primary	-2.806^{***}	(0.716)
Lower Secondary	-2.702^{**}	(1.094)
Upper Secondary	**[ref]**	
Certificate	1.493^{*}	(0.895)
Degree+	4.204^{***}	(0.682)
Residence 2015		
At Same Address	**[ref]**	
Elesewhere in County	5.707^{***}	(1.264)
Elsewhere in Ireland	3.895^{**}	(1.915)
Outside Ireland	-3.258^{**}	(1.374)
County of Residence		
Carlow	-0.199	(0.136)
Dublin City	**[ref]**	
South Dublin	0.0408	(0.0670)
Fingal	0.631^{***}	(0.107)
Dun Laoghaire-Rathdown	0.371^{***}	(0.0718)
Kildare	0.177	(0.125)
Kilkenny	0.231^{**}	(0.118)
Laois	-0.102	(0.132)
Longford	0.143	(0.158)
Louth	0.186	(0.137)
Meath	0.606^{***}	(0.160)
Offaly	0.224	(0.143)
Westmeath	0.0586	(0.139)
Wexford	0.104	(0.134)
Wicklow	0.540^{***}	(0.159)
Clare	0.153	(0.152)
Cork City	0.208^{**}	(0.0869)
Cork	0.181	(0.113)
Kerry	-0.423^{**}	(0.180)
Limerick City	-0.403^{***}	(0.112)
Limerick	0.194^{*}	(0.117)
Tipperary North	-0.295^{**}	(0.145)
Tipperary South	0.0825	(0.147)
Waterford City	0.369^{***}	(0.125)
Waterford	-0.295^{**}	(0.131)
Galway City	-0.461^{***}	(0.0925)
Galway	-0.0131	(0.142)
Leitrim	0.128	(0.197)
Mayo	0.0785	(0.193)
Roscommon	0.523^{***}	(0.175)
Sligo	0.445^{***}	(0.155)
Cavan	-0.115	(0.163)
Donegal	0.220	(0.263)
Monaghan	-0.226	(0.176)
Observations	18,641	

Notes: Standard errors allow for clustering at the county level. $^{*}p<.1$; $^{**}p<.05$; $^{***}p<.01$

results have been previously identified in the literature. Aguiar and Hurst (2005), for example, find that at retirement individuals reduce food expenditures while maintaining both the quality and quantity of consumption. The difference is attributable to an increased engagement with search. De los Santos (2018) further supports the result in his model of search cost heterogeneity. In our model, the effect of being retired offsets the age effect by almost half. A similar reduction in search costs might also explain the coefficient on areas inhabited by widowed individuals, where increased searches are expected by the model.

According to the model, higher local average educational attainment is strongly associated with more searches. An area where all residents are degree holders is expected to make about 4.2 additional searches per 100 HH in comparison to one where all residents have an upper secondary qualification. In light of the previously identified association between social class and search, as well as the likely correlations between education, income, and social class, this result now seems intuitive. Indeed, the pattern of coefficients here closely reflects that of the social class result in the previous model. One could, thus, posit similar underlying mechanisms. For example, the highly educated are more aware of the potential benefits from and are better equipped to navigate the complexities of the market.

As before, county controls are included in the model of individual characteristics. The scale of the marginal effects is limited among these variables and statistical significance is sporadic. Overall these controls present little evidence of noteworthy geographic patterns in search intensity by county.

4.3. Further specifications

The most general model that one can construct using our data includes both the set of variables which describes household characteristics as well as that which describes individuals. Such a model is reported in Table 6. By combining the two previous model specifications, we explore whether or not previously identified relationships are diminished by the presence of potentially correlated variables. While the likely collinearity between the regressors now makes interpretation somewhat more difficult, the overall results are broadly unchanged. Some of the previously noted associations are statistically weaker here. For example, some of the social class, employment tenure and education coefficients lose statistical significance. This is likely due to area level correlations in these variables. It is noteworthy, however, that the coefficient on "Degree+" in the education variable remains statistically significant and areas predominantly populated by social classes E, F, and I are still statistically expected to search less. This implies that some independent mechanisms are likely at play. The same may be posited of a relationship between age and family structure. In this model, one still expects, at the 95% confidence level, that areas populated by the over 65s will have fewer searches. However, the magnitude of the association is more than halved in comparison to the previous model. It is likely that when both sets of variables are included, the estimated coefficients are partly capturing the same variation in search intensity. Overall, however, the estimates do not give rise to a narrative that significantly deviates from that of the discussions earlier in this section.

Since all specifications presented are based on data with a strong spatial element, it is also necessary to give due consideration to the possibility of spatial dependence in the models. It is plausible that there exists patterns in search behaviour that spill over Small Area boundaries or that the socio-economic characteristics of a given Small Area could be associated with changes in search in closely neighbouring regions. In unreported robustness checks, we find little evidence that this is the case. We compute a number of uncensored spatial-econometric specifications accounting for various types of spatial dependence between a Small Area and its five nearest neighbours. The results did not vary significantly from those of the comparable non-spatial specification.

Table 6: Marginal effects from Tobit model regressing search intensity on all characteristics (Small Area shares)

Dependent Variable: Searches/100 HH	(3)	
	$\delta y/\delta x$	Robust SE
Broadband: NBP		
NBP Dark Blue	**[ref]**	
NBP Light Blue	-0.710^{***}	(0.140)
NBP Amber	-0.742^{***}	(0.190)
Broadband: SAPS		
Broadband Access	**[ref]**	
Other Access	-4.747^{***}	(0.407)
None	-2.646^{***}	(0.664)
Population Density		
Quintile 1	-0.325^{**}	(0.149)
Quintile 2	-0.207^{**}	(0.0814)
Quintile 3	**[ref]**	
Quintile 4	-0.136	(0.0866)
Quintile 5	-0.577^{***}	(0.0907)
Age Category		
Under 18	-1.554	(1.222)
18-24	1.187	(1.075)
25-34	-0.465	(1.033)
35-44	**[ref]**	
45-54	0.834	(1.039)
55-64	-0.964	(1.493)
65+	-3.818^{***}	(1.378)
Marital Status		
Single	**[ref]**	
Married	2.631^{***}	(0.812)
Separated	-1.866	(2.067)
Divorced	2.002	(2.640)
Widowed	2.512^{*}	(1.513)
Place of Birth		
Ireland	**[ref]**	
UK	-1.963^{*}	(1.190)
Poland	-1.582^{*}	(0.875)
Lithuania	-4.143^{**}	(1.818)
Other	1.053	(0.928)
ROW	-2.190^{**}	(0.952)
Family Structure		
Pre-family	2.455^{***}	(0.636)
Pre-School	2.750^{***}	(0.775)
Early School	2.288^{***}	(0.573)
Pre-Adolescent	1.557^{**}	(0.648)
Adolescent	0.981	(0.636)
Adult	**[ref]**	
Empty Nest	-0.149	(0.772)
Retired	-0.663	(0.881)
Housing Status		
House/Bungalow	**[ref]**	
Flat/Apartment	-0.774^{***}	(0.258)
Caravan/Mobile home	1.411	(1.837)
Not Stated	1.159	(1.173)
Commute Duration		
None	**[ref]**	
15-30 mins	1.196^{**}	(0.475)
30-45 mins	1.208^{***}	(0.377)
45-60 mins	0.546	(0.860)
60-90 mins	3.092^{***}	(1.163)
90+ mins	0.385	(1.497)
N.S.	3.098^{***}	(0.892)
Social Class		
A (Employers/Managers)	0.141	(0.870)
B (Higher Prof.)	-0.553	(1.305)
C (Lower Prof.)	0.194	(1.094)
D (Non-manual)	**[ref]**	
E (Manual skilled)	-2.083^{**}	(0.860)
F (Semi-skilled)	-1.958^{***}	(0.728)
G (Unskilled)	-0.707	(1.052)
H (Own A/c Workers)	-1.345	(0.889)
I (Farmers)	-5.538^{***}	(0.952)
Other	-2.384^{***}	(0.577)
Housing Tenure		
Owned Outright	**[ref]**	
Owner with Mortgage	1.592^{***}	(0.522)
Private Rental	-0.686	(0.608)
Local Auth. Rental	-0.873^{**}	(0.410)
Voluntary Body Rental	0.291	(0.554)
Free of Rent	-1.788	(1.552)
N.S.	-1.376	(0.938)
Employment Tenure		
Employed	**[ref]**	
Searching: First Job	-3.900	(2.376)
Unemployed	-0.183	(0.834)
Student	-1.406	(0.855)
Homeworker	0.127	(1.202)
Retired	3.476^{**}	(1.494)
Disabled	3.226^{**}	(1.347)
Other	0.488	(1.856)
Educational Attainment		
None/N.S.	-0.695	(0.859)
Primary	-1.797^{**}	(0.714)
Lower Secondary	-1.430	(1.123)
Upper Secondary	**[ref]**	
Certificate	1.284	(0.787)
Degree+	3.742^{***}	(0.767)
Residence 2015		
At Same Address	**[ref]**	
Elesewhere in County	5.170^{***}	(1.195)
Elsewhere in Ireland	3.762^{**}	(1.855)
Outside Ireland	-3.217^{**}	(1.256)
Observations	18,641	

Notes: Standard errors allow for clustering at the county level. $^{*}p<.1$; $^{**}p<.05$; $^{***}p<.01$

5. Future extensions

The main limitation of this analysis stems from the lack of individual-level data on the socio-economic and demographic characteristics of searchers. This limits the scope for exploring the effects of interactions among individual or household characteristics.

It remains a task for future work to identify the mechanisms that drive consumer search for telecoms services. In particular, a growing literature in behavioural economics has offered alternative mechanisms which may influence search behaviour. This research area, which is rooted in the field of psychology and studies systematic behavioural deviations from traditional economic models of rationality, arguably has broad implications across various market contexts, not least the market for telecommunications products and services (Lunn, 2012). The propensity to engage in active search may be affected by numerous behavioural findings. For example, if a potential searcher is relatively disinclined to search when their pre-search expectations of the potential he/she gains from doing so do not significantly exceed the experienced utility from a current contract, then an endowment effect (Kahneman, Knetsch, & Thaler, 1990; Knetsch, 1989) could be at play. Similarly, if the perceived potential gains are above a threshold that should encourage action, but a consumer still does not search, then this could be seen as consistent with behavioural models of procrastination (O' Donoghue & Rabin, 2001). Work on default options (Madrian & Shea, 2001) may also be relevant. If a consumer's current contract ends but there exists a passive default to remain with their supplier, then they could lack the encouragement needed to engage in active search. While these and many other behavioural findings have plausible impacts on individual propensities to search, there is a lack of evidence suggesting socio-demographic differences in their influence. Since the relationship between our results and behavioural economics and cannot be stated with certainty, an exploration of this type is left for future work.

6. Conclusions

We contribute to the literature by exploiting geographic variation in consumer search activity to gain an understanding of the average demographic and socio-economic characteristics of those who search for retail broadband services in Ireland. A unique and novel dataset from a commercial price comparison website, Bonkers.ie, provides a rich source of actual online search information on which we can base our analysis. By linking this geo-coded search intensity to spatially dis-aggregated census data we are able to profile who is searching the most and thus, to whom the potential benefits of search are most likely to accrue. The analysis yields a number of interesting, policy-relevant results.

We find that while lack of access to high-speed broadband reduces consumer search, the magnitude of the effect is relatively small. This implies that completing the national rollout of these networks through the National Broadband Plan should lead to modest increases in search intensity. A larger effect arises from less than full adoption of broadband even in places where it has been available for some time. Those who choose not to use these services will obviously not make much use of price comparison tools.

Our main finding is that search intensity varies significantly across socioeconomic and demographic groups. We find that the frequency of search is significantly higher in areas with many highly educated, married people, commuters, mortgage holders, and retirees. In contrast, the frequency of search is decreased in areas with many older residents, farmers, low-skilled workers and students.

While data limitations prevent us from examining the relationship between search and household income directly, the pattern of effects is suggestive of a positive relationship between economic means and search intensity. If more advantaged groups in society participate more actively in search and switching behaviour, price discrimination by suppliers in favour of more active consumers compared to inert ones could lead to a further source of disadvantage for vulnerable groups.

It remains for further work to establish whether this pattern of effects is common across jurisdictions and how stable it is over time as retail telecoms markets evolve. It is also worth considering the mechanisms underlying group-level variations in search and switching propensities and to consider what potential informational or behavioural interventions may have to increase the engagement of disadvantaged groups in consumer search activities.

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